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Research article

A data - Model fusion methodology for mapping bushfire fuels for smoke emissions forecasting in forested landscapes of south-eastern Australia

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ABSTRACT

The increasing regional and global impact of wildfires on the environment, and particularly on the human population, is becoming a focus of the research community. Both fire behaviour and smoke dispersion models are now underpinning strategic and tactical fire management by many government agencies and therefore model accuracy at regional and local scales is increasingly important. This demands accuracy of all the components of the model systems, biomass fuel loads being among the more significant. Validation of spatial fuels maps at a regional scale is uncommon; in part due to the limited availability of independent observations of fuel loads, and in part due to a focus on the impact of model outputs.

In this study we evaluate two approaches for estimating fuel loads at a regional scale and test their accuracy against an extensive set of field observations for the State of Victoria, Australia. The first approach, which assumes that fuel accumulation is an attribute of the vegetation class, was developed for the fire behaviour model Phoenix Rapid-Fire, with apparent success; the second approach applies the Community Atmosphere Biosphere Land Exchange (CABLE) process-based terrestrial biosphere model, implemented at high resolution across the Australian continent. We show that while neither model is accurate over the full range of fine and coarse fuel loads, CABLE biases can be corrected for the full regional domain with a single linear correction, however the classification based Phoenix requires a matrix of factors to correct its bias. We conclude that these examples illustrate that the benefits of simplicity and resolution inherent in classification-based models do not compensate for their lack of accuracy, and that lower resolution but inherently more accurate carbon-cycle models may be preferable for estimating fuel loads for input into smoke dispersion models.

1. Introduction

Globally, the burning of vegetation is a major source of trace gases and particulates to the atmosphere and a major pathway for returning carbon from organic combination to the atmosphere, mainly as carbon dioxide. The smoke emitted in vegetation fires has extensive health and economic impacts with fine particles ($PM_{2.5}$) in particular becoming a pollutant of concern for the health of regional populations (Dymond et al., 2004; Haikerwal et al., 2015). Other smoke pollutants harmful to human health include carbon monoxide (CO), organic compounds, ozone (O_3) and secondary organic aerosols (Kochi et al., 2010). The smoke from vegetation fires contributes to regional haze, reduces visibility and can disperse over long distances impacting human populations far from the smoke source (Koe et al., 2001).

Since the year 2000 the scale of burning in southern Australia has been large, with more than 1.2 M ha of *Eucalyptus* open forests treated with planned fire and 3.6 M ha burnt in wildfires (ABARES, 2013). The policy to increase the current rate of planned burning poses significant challenges for regional managers if smoke and pollutant impacts on population health are to be mitigated (Meyer et al., 2013). Smoke dispersion models are required to forecast medium to long distance transport of smoke constituents and their potential surface impacts on community and industry (Wain et al., 2008).

Both the type and amount of fuels affect smoke and emission during forest fires (Russell-Smith et al., 2009; Weise and Wright, 2014). Fine fuels (leaf litter, bark and small twigs with diameter < 6 mm) are usually burnt in flaming combustion and affect progression of the flaming front of a surface fire. Therefore fine fuels are inappropriate for estimating fire effects associated with post-frontal, smouldering combustion, a characteristic of heavier fuels such as coarse woody debris [CWD] (Cook and Meyer, 2009). In North America, fuels are grouped in complex fuel beds and include duff, fine litter fuels, coarse woody fuels

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of various diameter classes, grass, shrubs, understorey and canopy fuels (e.g. Fuel Characteristic Classification System, Ottmar et al., 2007). After selecting appropriate fuel bed characterization, such as amount (loading, kg m^2), density, and surface area to volume ratio, land managers apply a suite of models, including the emission model CONSUME (Ottmar and Prichard, 2008) to predict the smoke emissions, and the dispersion models available in the Bluesky framework (https://www.airfire.org/bluesky) to predict the smoke dispersion. In south-eastern Australia, fuel characterization research has focused on providing inputs for predicting fire spread (e.g. McArthur Meter and Phoenix fire spread model) and as such has focused on fine fuel components (Cruz et al., 2015; McArthur, 1967).

In contrast to fine fuels, the contribution of CWD, especially large woody fuels, to surface fire intensity in Australia is commonly ignored in fire behaviour models. Yet combustion of CWD contributes to total energy release, fire-line intensity, burn severity, burn depth, difficulty of suppression, total radiant heat flux and firefighter safety (Sullivan et al., 2002). CWD can smoulder for days and weeks releasing a complex mixture of gases and particulate matter (Reisen et al., in submission) and greatly contributing to the total fire emission (Volkova et al., 2014). Despite this, the quantification and mapping of CWD fuels in south-eastern Australia remains understudied. Nevertheless, the emerging requirement for accurate emission and dispersion prediction requires a system for mapping both fine and CWD fuels.

The most common approach for describing fuel loads has been association, in which fuel information is assigned to existing vegetation classifications and subsequently mapped (Keane, 2013). Depending on the design and intended application of the vegetation classes, for example the relative emphasis on floristic and structural characteristics, secondary attributes of the classes can sometimes be derived from a relatively small number of field measurements in each class. The accuracy of the association depends on correlation strength between the fuel attribute and the vegetation class (Keane et al., 2006). Classifications based on vegetation properties can be specifically designed to optimise the correlation between an attribute and the vegetation class (Keane, 2013). There are many examples from around the world where this has been done at multiple scales, including for the major vegetation types of Greece (Dimitrakopoulos, 2002), Canada (Hawkes et al., 1995) and the United States (Reinhardt et al., 1997). In south-eastern Australia, a vegetation association approach was applied in the Phoenix Rapid Fire model (Tolhurst et al., 2008). Thirty eight fuel groups, including all the categories of native grasslands, shrublands, forests and plantations, were derived from the aggregation of over 600 Ecological Vegetation Classes (DELWP, 2016) – using vegetation composition, vegetation structure and physiographic location (Tolhurst, 2005 unpublished; Table S1). These fuel groups were then assigned a fuel load including values for surface, elevated and bark fuels, based on limited field sampling and literature review.

A separate approach to fuel-load mapping is based on ecological processes (biogeochemical modelling), rather than solely on correlation with vegetation types. Biogeochemical modelling relates fuel load to the balance between primary production of live biomass and its removal through mortality to form dead organic matter (DOM), the incorporation of the DOM into soil and litter pools, and removal of DOM by decomposition. For example, the CABLE terrestrial biosphere model that has been used to assess Australian continental (Haverd et al., 2013a; Trudinger et al., 2016) and global carbon budget dynamics (Le Quéré et al., 2016), generates two structural fuel pools (fine litter and CWD) that approximate the fine and coarse fuel loads required for modelling of smoke dispersion.

The classification and biogeochemical modelling approaches for fuel load mapping each have strengths and weaknesses. The strength of classification based mapping is that the fuel map resolution is limited only by the resolution of the vegetation mapping, and in many cases, vegetation maps are produced at very high spatial resolution. If the fuel map is to be accurate then the correlation between the attribute (fuel load) and the class must be strong and stable. However, these attributes can be evaluated from field monitoring of well-defined sites, and updated as necessary, and therefore a relatively small field measurement program can produce a high resolution fuel load map. Further, when land use change and the impacts of natural events (e.g. fire, storms, floods) change the vegetation patterns, fuel load maps are automatically revised in line with the vegetation maps. This is a routine exercise for land-use and vegetation mapping based on remote sensing. The weakness is that fuel load dynamics measured in the field programme are fixed in time and therefore do not reflect climate variability. In the case of the Phoenix model, the fuel attribute linked to vegetation classes is fuel accession rate (defined by the rates of litterfall and fuel decay). Fuel load is calculated from the accession rate and the local fire history. The strength of the biogeochemical modelling approach is that it is based on known and verified ecological processes driven by measurable inputs, and is fully dynamic and consequently has a fine time resolution; for most processes the appropriate temporal resolution should be hours to days. However, the spatial resolution of the model is limited by both the resolution of the input data, and the computational demands. In most cases the practical resolution is $0.05^\circ \times 0.05^\circ$. Whether this resolution is suitable for smoke emission and dispersion modelling will depend on the application; for example, it may not be adequate for fine scale impact modelling to predict plume strike on individual facilities (e.g. hospitals). The lower spatial resolution of biogeochemical models may be sufficient for assessing regional carbon dynamics, smoke scenarios and biogeochemical cycles (Fleming et al., 2015; Running et al., 1989). However, the biggest weakness of both types of Australian fuel load mapping models described above is that most of the assumptions establishing the Phoenix fuel groups and their parameters, and the CABLE estimates, have not been tested at the regional spatial scale, principally because there are few datasets of reliable fuel load measurements at the required spatial scale.

The need for accurate smoke dispersion forecasting in southern Australia, based on best available fuel load mapping of fine and CWD fuels, has assumed a high priority due to the catastrophic fire regimes of the last decade (Keywood et al., 2015). The development of a prototype smoke forecast modelling framework became a highest priority for the land management agency of Victoria (Cope et al., 2016). The smoke forecasting model builds upon a number of components, with bushfire fuel load maps of fundamental importance. In the absence of CWD fuel load maps for the Phoenix Rapid fire predictions, and because of the limitations of Phoenix fuel maps described above, we were assigned the task of developing fuel load maps for operational use in smoke dispersion models from forest fires in Victoria. Here we describe a hybrid methodology that combines the vegetation association approach of the Phoenix model with continuous modelling of fuel load (CABLE), which we calibrate against a geographically extensive field dataset. This methodology provides fine and CWD fuel load estimates to a smoke emissions model now being applied by Victoria's Emergency Services to forecast the dispersion of smoke from fuel reduction burning and bushfires.

2. Experimental design and methods

2.1. The study area

All data were collected from forest sites across the 7.12 M ha of public forests and parks, extending from latitude 39°–36° S and longitude 142°–144° E, in the State of Victoria, Australia. These forests are dominated by the genus *Eucalyptus,* of which there are about 100 species in the State, and occur over 400–1500 mm per annum rainfall range and average winter and summer temperatures between 8° and 20 °C.

2.2. Datasets and approach

The elements of the study included 3 sets of fuel load data: 1) inferred fuel load for each of the Phoenix model fuel groups (surface fuels only, Supplementary, Table S1); 2) the CABLE predicted fuel loads (fine and CWD) and, 3) an empirical dataset of fine and CWD fuel loads from a number of locations across Victoria (331 locations for fine and 472 locations for CWD, Supplementary, Fig. S1). The biogeochemical model CABLE was used as the basis for fuel map development. For the locations with empirically measured fuels, model estimates were clustered by the Phoenix fuel groups and calibrated against field observations using linear regression. An independent subset of field measurements was withheld for the validation process.

2.2.1. Datasets

2.2.1.1. Phoenix Rapid Fire fuel groups. Phoenix Rapid Fire is a dynamic fire behaviour and characterization model used in fire-response operations in south eastern Australia (Tolhurst et al., 2008). A steady-state surface fuel load estimate is assigned to each fuel group. When applied in Phoenix to model fire progression, the steady state fuel load is first adjusted for fire history using a fuel accumulation curve to estimate actual fuel load at the time of the fire. Only thirty five fuel groups relevant to grasslands, shrublands and forests were used in this analysis of the data and for the development of fuel load maps, while the remaining three fuel groups (plantations, no vegetation) were excluded (Supplementary, Table S1).

2.2.1.2. Biogeochemical model CABLE - BIOS2. BIOS2 is a fine-spatial-resolution ($0.05° \times 0.05°$) offline modelling environment, including a modification of the CABLE biogeochemical land surface model (Wang et al., 2011) incorporating the SLI soil model (Haverd and Cuntz, 2010). BIOS2 parameters are constrained and predictions are evaluated using multiple observation sets from across the Australian continent, including streamflow from 416 gauged catchments, eddy flux data (CO_2 and H_2O) from 12 OzFlux sites, litterfall data, and soil, litter and biomass carbon pools (Haverd et al., 2013a). The meteorological inputs to BIOS2 include gridded rainfall, temperature, vapour pressure and solar irradiance surfaces, each downscaled to hourly time steps, from the Bureau of Meteorology. Soil information is derived from 725 principal soil types defined in the Digital Atlas of Australian Soils. Vegetation cover is sourced from the GIMMS3g FAPAR product (Zhu et al., 2013) and partitioned into either woody and grassy vegetation layers with an assigned leaf area index. A set of carbon pools is assigned to these layers. The grass layer has two pools-structural and metabolic leaf carbon; the woody layer has three pools-structural and metabolic leaf carbon and CWD. We assign the four grassy and woody leaf carbon pools to the fuel class “fine fuel” and we assign the CWD pool which includes fallen dead branches, logs and standing dead trees to “coarse fuels”. BIOS2 predictions for the period of 1983–2013 were used to extract fine and coarse fuel load, and the 30-year mean of the annual monthly means were analysed using ArcGis (Esri, Redlands, CA, USA).

2.2.1.3. Empirical datasets. All field observations of fuel load were sourced from three field programs: (1) a dataset collected for a program of the Bushfire Cooperative Research Centre by Volkova and Weston (V–W); (2) the Victorian Forest Monitoring Program (VFMP); and (3) a CWD data set collected in old-growth *E. regnans* forest (ER). About 500 georeferenced fuel load observations were identified as suitable (Fig. 1).

The V&W dataset of 56 plots was collected between 2011 and 2013. Measurements comprised the classes defined by IPCC (2003): litter comprising fallen fruit, leaves, bark, and small branches with diameter < 25 mm including duff (partly decomposed leaf organic material) and CWD comprising woody materials on the forest floor with diameter ≥25 mm. Litter was further separated into fine litter (diameter < 6 mm) and twigs (diameter 6–25 mm) to better reflect common fine fuel size classes applied in fire behaviour research in southern Australia. The method for sampling and estimating biomass is described in detail in Volkova and Weston (2013, 2015).

The VFMP dataset included fine and CWD fuel load collected between 2011 and 2014 from 419 sites (Haywood et al., 2016). The fine fuels comprised of duff, leaves, bark and twigs less than 10 mm in diameter. Within each sample plot litter load was measured in four $0.5\,m^2$ sampling quadrats. CWD fuels were branches and logs with diameters greater than 100 mm that were detached from the trees of their origin and in contact with the ground. Each CWD piece was assigned a decay class of either sound, moderate, rotten or very rotten (DSE, 2012). The diameter and length of all CWD elements in each plot was also measured, from which CWD volume was estimated assuming each element was cylindrical. Volume was converted to mass assuming wood densities for each decay class of $451\,kg\,m^{-3}$ (sound), $340\,kg\,m^{-3}$ (moderate decay), $226\,kg\,m^{-3}$ (rotten) and $100\,kg\,m^{-3}$ (very rotten, Volkova and Weston, 2013).

The ER dataset comprised measurements from 27 locations in old-growth *E. regnans* forests near Kinglake, Victoria, collected in 2008. For this project, CWD was defined as woody material on the forest floor with diameter ≥25 mm. Data was collected using a line intersect method (Van Wagner, 1968) with transect length of 30 m–70 m. The percentage decay was recorded for each measured CWD piece and the CWD load was estimated following Volkova and Weston (2013, 2015).

2.2.1.4. Harmonisation of empirical datasets to uniform values. The VFMP dataset did not include the CWD with diameter between 10 mm and 100 mm (Table S2). Therefore, to align the VFMP dataset with the V&W and ER datasets, the VFMP data was scaled by the ratio of fine twigs (6–25 mm), CWD with diameter 25–100 mm ($CWD_{d=\ 25\text{–}100\ mm}$) and CWD with d > 100 mm ($CWD_{d\ \geq\ 100mm}$) to the total CWD in the V&W dataset (Table 1).

The V&W data samples were from vegetation classes similar to the VFMP dataset and therefore it was reasonable to assume that the ratios between size classes observed in V&W also apply to the VFMP sample sites (Fig. 1).

For sites sampled less than 20 years after fire, the observed fuel load (fine and CWD) were adjusted to an equilibrium value using the fuel recovery curves for fine fuels derived from a comprehensive literature review developed as a part of the national revision for estimating emission from fires on forest lands in southern Australia (Supplementary, Table S2). The literature review has identified that predictions based on CWD fuel accumulation curves didn't produce reliable estimates of CWD loads and therefore it was recommended to use the same parameters for both fuel types (Roxburgh et al., 2015).

2.2.2. The analysis of fine and coarse fuel loads predicted by each model

The fuel maps underpinning the Phoenix Rapid Fire and BIOS2 predicted fuel load values were overlaid onto geo-referenced field data. Field measured fuel load (observed) at each sample location was thus supplemented with the spatial attributes of BIOS2 fuel load (predicted), Phoenix fuel load (inferred from vegetation class) and Phoenix fuel group assessed against a 1:1 line. These data samples were then aggregated by the Phoenix fuel groups. Because field data was unevenly distributed among Phoenix fuel groups, the data were first checked for normality and subsequent analyses were based on fuel group means.

The least - squares model approach was applied to improve BIOS2 model predictions. The best-fitting line for the observed data was calculated by minimizing the sum of the squares of the vertical deviations from each data point to the 1:1 line. Slope and an intercept of the linear regression were estimated using a Solver function (Frontline Systems Inc. Incline Village, NV, USA) embedded within Microsoft Excel 2010, based on the minimal sum of squared deviations (SSDs) between observed and predicted fuel load. A liner regression model of SigmaPlot 13.0 (Systat Software, Inc. San Jose, California, USA) was applied to the observed and predicted values to derive significance of the relationship

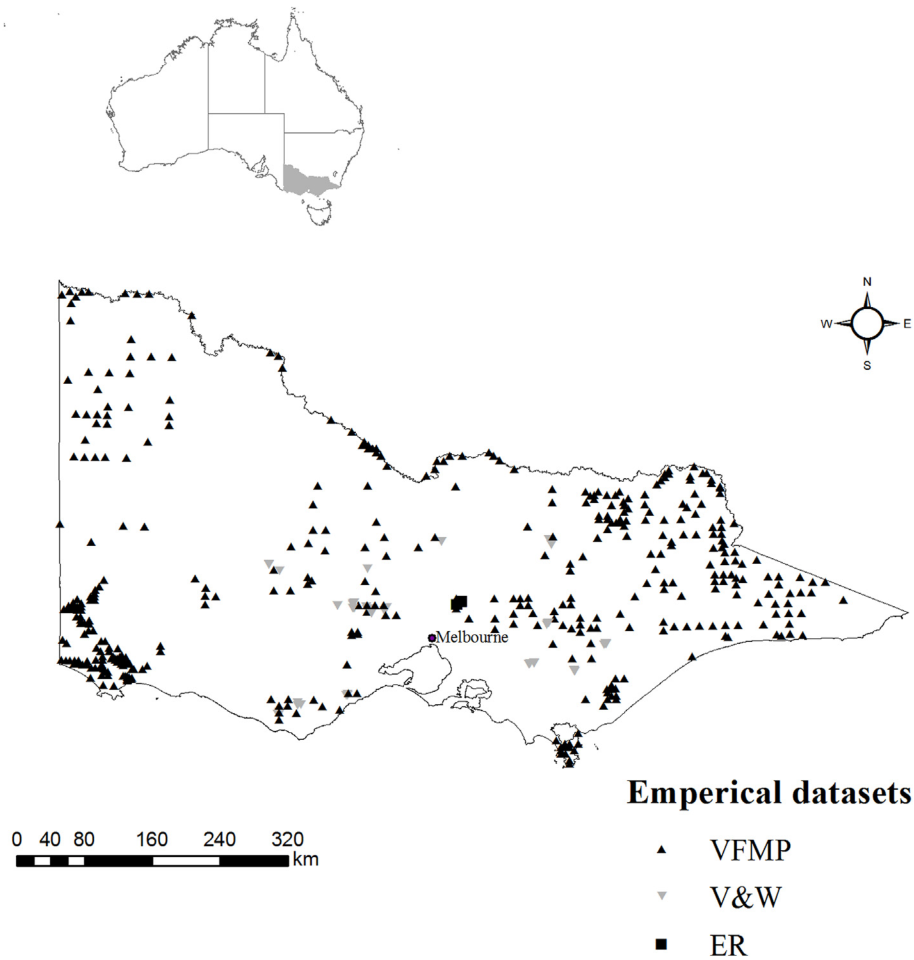

Fig. 1. Map of Victoria showing the field collection points by the datasets, where: closed triangle is the VFMP dataset, grey reversed triangle is the V&W dataset and square is the ER dataset.

Table 1
Adjustment factors for missing CWD categories in the VFMP data based on 56 sampling locations from Volkova and Weston dataset.

CWD pool	Load, Mg ha^{-1}	%	Scaling factor
Twigs (6–25 mm)	3.0 ± 0.48	12.2	$CWD_{100+\ mm}$ × (12.2/52.8)
$CWD_{25–100\ mm}$	7.1 ± 0.71	35.0	$CWD_{100+\ mm}$ × (35.0/52.8)
$CWD_{100+\ mm}$	17.6 ± 2.41	52.8	
Total	**28.0 ± 3.02**	**100**	

(P-value) and the coefficient of determination (R^2) for each of the models (BIOS2 and Phoenix). Additionally, the biases in each of the fuel estimators was corrected by quantifying the bias by fuel class (fine and coarse) using a randomly selected subset of the empirical dataset and comparison of the corrected model predictions against observations for sites not used to determine the bias values.

3. Results

A total of 483 of the fuel sampling sites were included in the

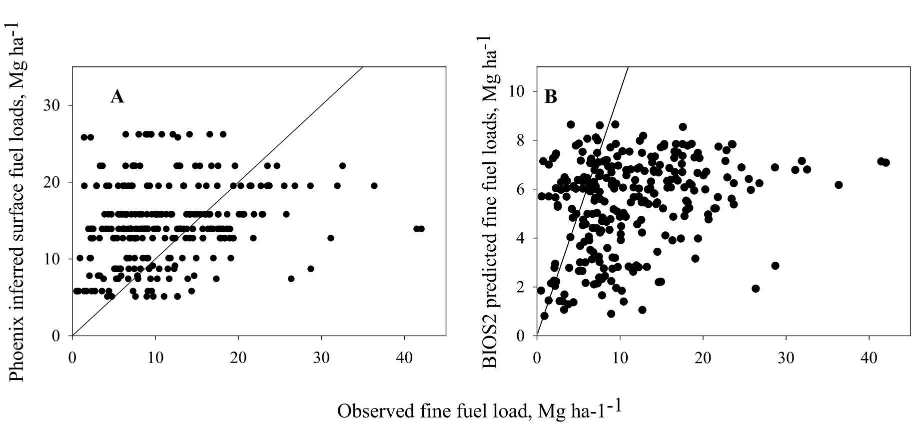

Fig. 2. Observed fine fuel loads plotted against A) Phoenix inferred and B) BIOS2 predicted values. Black line is 1:1. Each dot represents individual measurement, n = 275.

analysis: 288 sites with both fine and CWD measurements, 176 sites with CWD fuel load estimates only, and 29 sites where only fine fuel load was measured (Fig. S1). Sixty (~20%) of the sites with both fine and CWD fuel load data were randomly selected as validation data and excluded from the main analysis.

3.1. Fine fuels

Individual observations of fine fuels were compared with Phoenix inferred fuel load values (Fig. 2A) and BIOS2 predicted values (Fig. 2B). The Phoenix inferred fuel loads were relatively evenly distributed around the 1:1 line up to about 20 Mg ha^{-1} of observed fuel values, and fell below the line in the range 20–40 Mg ha^{-1} (Fig. 2A). Based on correlation with unaggregated field observations, the Phoenix inferred estimates explained about 6% of variability in fine fuel loads ($R^2 = 0.056$, $P < 0.0001$). In contrast, the BIOS2 model mostly underestimated fine fuel load across the full range of the field observations as the maximum BIOS2 prediction of 9 Mg ha^{-1}, is substantially lower than the maximum observed fuel loads (Fig. 2B). BIOS2 explained about 8% of fine fuel load variability ($R^2 = 0.076$, $P < 0.0001$).

Individual observations were aggregated by the Phoenix fuel groups. The analysis dataset fell within 23 of the Phoenix fuel load groups, seven groups had fewer than three observations and three (F08 'Forest with shrub', F09 "Forest herb-rich' and W07 "Woodland Heath") had more than 30 measurements each. Twelve Phoenix fuel groups contained no field measurements and therefore could not be analysed. The descriptive statistics (mean, median, maximum) of observations, and model predictions are presented in detail in Table S4 of the Supplementary data. The group means of observations and model predictions are compared in Fig. 3.

Fuel loads assigned to the Phoenix fuel groups were comparable to the average and maximum values of field observations, while BIOS2 predictions were distributed more uniformly than field measurements (Table S4). Averaging individual field measurements by fuel groups showed that Phoenix fuel loads had more parallel rather than uniform distribution of the data along 1:1 (Fig. 3A, $R^2 = 0.16$, $P = 0.054$). BIOS2 tended to under-predict fuel loads with the majority of the observed fuel loads lying below the 1:1 line (Fig. 3B, closed symbols, $R^2 = 0.35$, $P = 0.003$) – a data pattern showing that a single linear regression adjustment of the model was possible.

The minimum sum of squared deviations (SSD) between observed and BIOS2 predicted fine fuel load was 779 (Table S5). A linear regression with an intercept of 4.036 and a slope of 1.115 reduced SSD to 258 (Table S5). This single scaling factor was applied to the model adjustment.

Scaling the BIOS2 predicted values, aggregated by Phoenix fuel groups, resulted in more evenly distributed data along the 1:1 line (Fig. 3B open symbols), demonstrating that a single bias correction is sufficient. The effect of this correction on BIOS2 predicted fuel load distribution in Victoria is shown in Fig. 4.

3.2. CWD fuels

CWD is predicted by BIOS2, however Phoenix addresses only the fuel categories that determine fire spread (surface, elevated and bark). The BIOS2 estimates of CWD fuel load range from ~1 Mg ha^{-1} to approximately 50 Mg ha^{-1}; this is a much smaller range than the observed fuel loads from 0.07 Mg ha^{-1} to an upper limit of 323 Mg ha^{-1} (Fig. 5A). The variability of CWD field observations is large, far higher than fine fuels. The relationship between observed and predicted values produces $R^2 = 0.137$ ($P < 0.001$).

The 410 field observations of CWD fuel load corresponded to 27 fuel groups; with some fuel groups having fewer than three observations and others having above 30 replicates (Table S6). Eight Phoenix fuel groups were not represented in the CWD analysis. When CWD loads were aggregated by Phoenix fuel group the relationship between observed and predicted values improved with $R^2 = 0.223$ ($P = 0.01$, Fig. 5B, closed symbols).

Removing the disparity in spatial scales between observation and model prediction reduced the variability. The least squares model with an intercept of 7.420 and a slope of 1.177 reduced SSD from 21884 to 18497 (Supplementary, Table S7). Scaling BIOS2 with an included offset resulted in closer agreement between predictions and observations but did not substantially correct the data distribution along 1:1 line (Fig. 5B open symbols).

A single scaling factor was used for calibration of BIOS2 for the development of the final CWD fuel load map in the same manner as for the fine fuels (Fig. 6).

4. Discussion

In this study we evaluated two approaches for developing fuel load maps for smoke emission and dispersion models and found that a combination of the vegetation association approach of the Phoenix model with the continuous modelling of fuel load (CABLE), calibrated against a geographically extensive field dataset, was the most appropriate. The developed methodology provides a transparent approach that can be continuously improved with additional field data to strengthen the correlation of predicted fuel loads with observed fuel loads. This method, and the fine and CWD fuel maps derived from it, addresses an immediate need for comprehensive bushfire fuel models based on empirical data, for smoke forecasting in Victoria, where, despite decades long research in bushfire fuels such models are not available. This contrasts to the comprehensive fuel knowledge datasets available for the fire-prone areas of the USA (Ottmar et al., 2007; Sandberg et al., 2001) and Canada (Kurz et al., 2009), as well as the savannah regions of northern Australia. In the latter, more than a decade-long program of fuel load observations (Russell-Smith et al.,

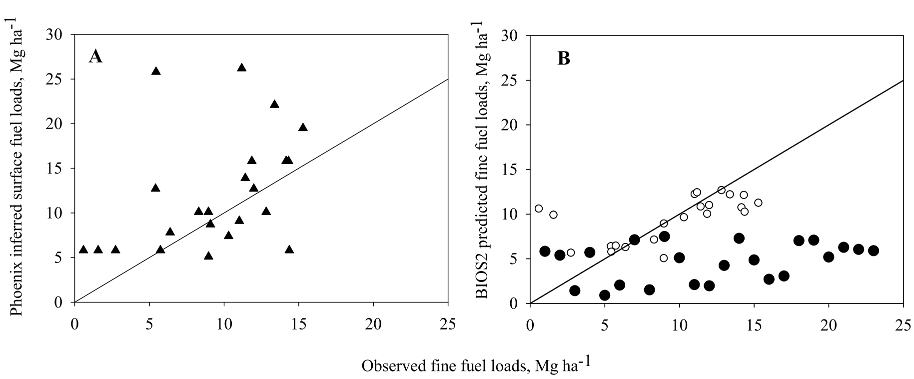

Fig. 3. Observed fine fuel loads plotted against A) Phoenix inferred and B) BIOS2 predicted fine fuel loads; closed dots before model correction and open dots after correction. Black line is 1:1. Each dot represents averaged fuel load aggregated by Phoenix fuel group, n = 23.

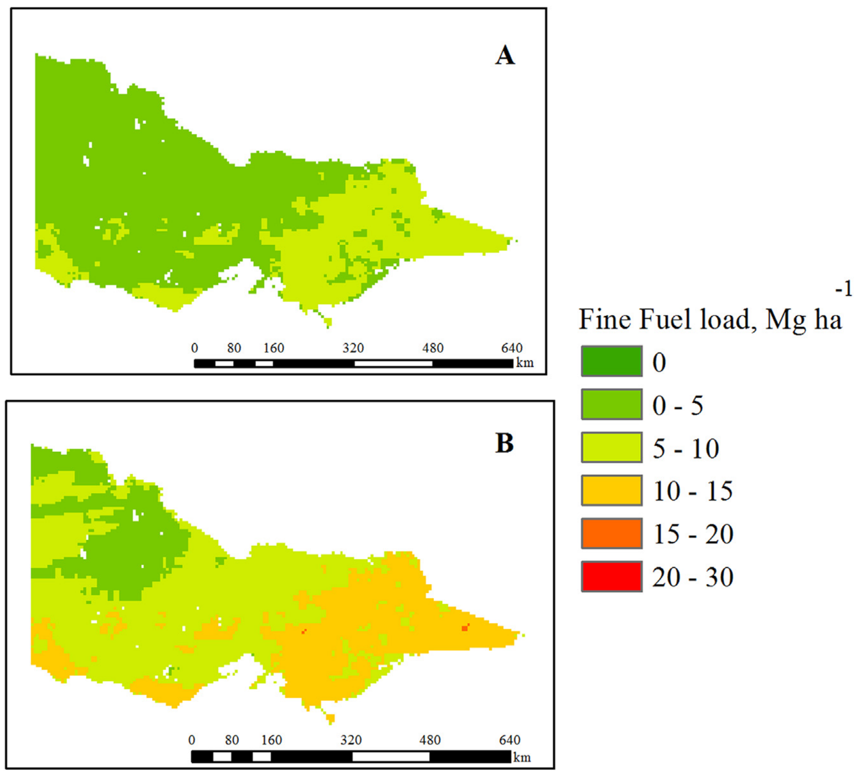

Fig. 4. Mapping fine fuel loads for Victoria. A) A map of fine fuel loads predicted by BIOS2 before calibration and B) Final fine fuel load map after a single scaling factor was applied. Map resolution is 0.05° × 0.05°.

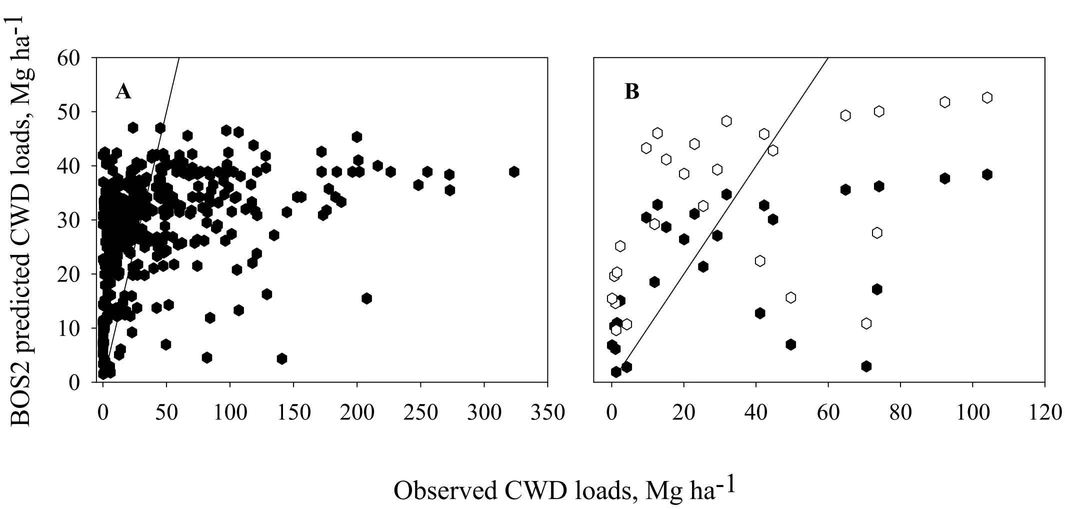

Fig. 5. Observed CWD fuel loads plotted against BIOS2 predicted, A) Individual measurements; n = 389; B) Aggregated by the Phoenix fuel groups, n = 27. Solid line is 1:1. Closed symbols before correction, open symbols after the model adjustment.

2009) has substantially improved the accuracy of smoke prediction modelling (Meyer et al., 2008).

A common problem in comparing point observations with model predictions is the disparity in scales. The low correlation we find between observations and predictions at point locations, demonstrate that point by point comparisons are of limited value for model validation. This lack of correlation is probably due to the large difference in the resolution of the models compared to the size of observation points; the, field observations are made at quadrat scale (m^2), the BIOS2 predictions are for 2500 ha grid cells and Phoenix predictions are attributes of the vegetation class (100 s km^2 coverage). An alternative to point by point comparison that addresses the scale issue is to aggregate the observations by fuel groups and to compare the descriptive statistics of observations and model prediction in each group. With limited fuel load observations, deriving a vegetation classification for fuel classes using statistical techniques is very challenging and instead, we relied on the expert knowledge of field ecologists who have extensive field experience to group the EVCs into common fuel classes, i.e. the fuel load groups of the Phoenix model. This proved to be a practical solution for the operational needs of the management agencies. Tailored additional field observations would allow a more robust statistical classification approach to be implemented for future updates.

There are strengths and weaknesses of both fuel prediction approaches used in this study. The strength of the biogeochemical modelling is that it is based on known and verified ecological processes driven by measurable inputs, and is fully dynamic and consequently has

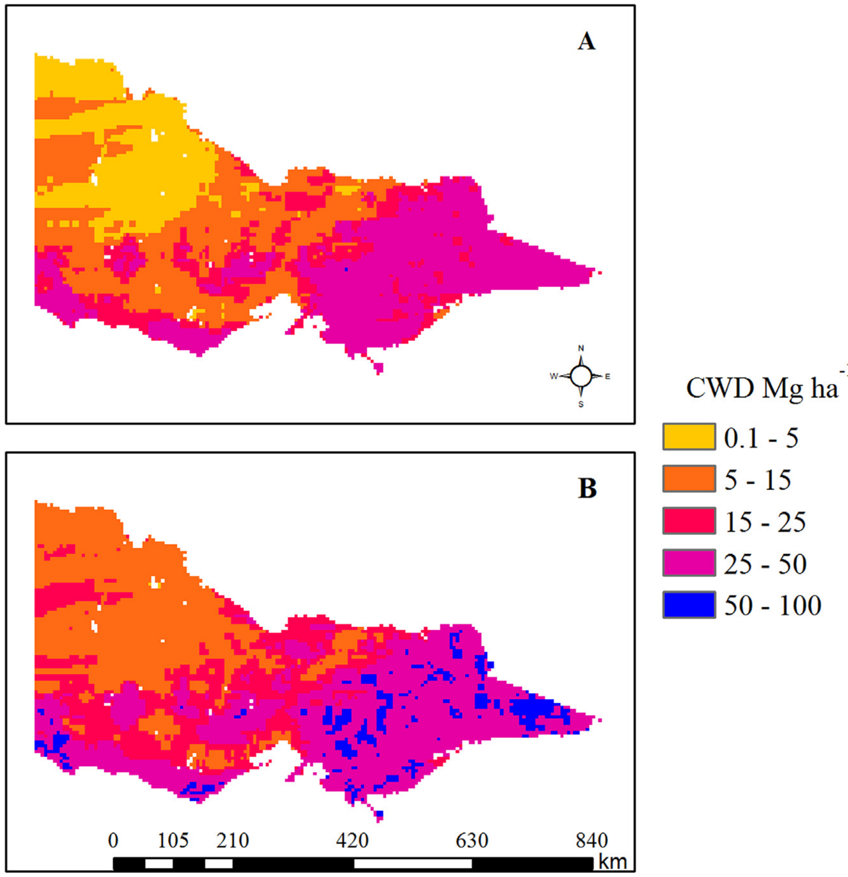

Fig. 6. Mapping CWD fuel loads for Victoria. A) A map of CWD fuel loads predicted by BIOS2 before calibration and B) Final CWD fuel load map after a single scaling factor was applied. Map resolution is 0.05° × 0.05°.

a fine time resolution. Therefore the CABLE fuel predictions address trends in climate-induced changes in fuel dynamics and are responsive to anomalous weather patterns as a part of the model design. However, the spatial resolution of the model is limited by the resolution of the input data which is 0.05° × 0.05° for the Australian continent (Haverd et al., 2013b) – such resolution is rather coarse as it doesn't reflect topographic variability and spatial heterogeneity of fuels.

Although the surface fuel maps underpinning the Phoenix Rapid Fire model have been widely adopted for operational use by New South Wales, South Australia and Tasmania, we believe that a transparent, updateable methodology that is sensitive to climate variability is required to progress bushfire fuel research in south-eastern Australia. For example, ideally the inferred fuel loads and fuel accumulation parameters applied to derive Phoenix fuel groups would be periodically updated and validated with field testing to improve their accuracy and to account for variability in climate. This is addressed in part where the fuel accumulation and fuel load parameters of the Victorian version of the Phoenix model were modified by other States through limited field surveys and review of the literature for more recent fuel parameter estimates (Watson, 2012; Watson et al., 2012). However, fuels relate not only to vegetation but to other important biophysical processes such as climate which affect rate of decomposition (Paudel et al., 2015). In the case of the Phoenix fuel mapping, the fuel attributes are linked to fuel accession rate (litterfall) and fuel decay rate; currently these are both constant parameters in the model, with fuel load calculated form these parameters and known fire history. It is likely the Phoenix fuel accumulation curves and equilibrium fuel loads require periodic revision to adjust for trends in climate and climate anomalies, as both mean annual rainfall and temperature have a strong influence on fuel accumulation parameters (Thomas et al., 2014).

While the vegetation-fuel association assumptions of the Phoenix fuel groups have not been extensively tested in the field, we believe that aggregation of more than 600 vegetation classes into 38 bushfire fuel groups, based on physiographic region and vegetation structural type, was the essential component for the development of fuel maps. Aggregating predicted fuel loads by vegetation classes showed a clear bias in BIOS2 model prediction that was possible to adjust with a single correction. A major limitation of the analysis was the uneven distribution of both fine and CWD fuel load data by vegetation classes, with over 30 observations for one fuel group and one or none for other fuel groups. It is likely that additional sampling in under-represented fuel groups would strengthen the correlation between observed and predicted fuels and improve fuel load prediction. While the available data revealed a clear linear relationship between observed and predicted fine fuel, CWD fuels were more scattered and could not be significantly improved by applying a linear adjustment. For this reason further refinement of the map is required to improve CWD fuel load predictions. Previous studies show that CWD is a difficult fuel type to predict due its sensitivity to choice of sampling method (Woldendorp et al., 2004), its inherently high spatial variability (Woldendorp and Keenan, 2005), and due to anthropogenic factors such as fuel wood removals. Additionally, inconsistencies in CWD fuel definition and sampling methods, identified in this study, became a major difficulty when compiling fuel data from various sources. Several different definitions for the size-range of CWD fuels were identified (i.e. diameter ≥6 mm; ≥25 mm or ≥100 mm); to address this all fuel load data was harmonized using simple ratios between size classes that were calculated from a set of 42 sites where all diameter classes were measured simultaneously. This is not ideal, because such ratios are inherently variable among forest types, and hence such conversions add uncertainty to the results. To improve this situation it is recommended that nationally consistent fuel class measurement methods are adopted,

as recommended by Gould and Cruz (2012).

Planning and implementation of prescribed burning requires understanding of the potential impact of smoke on air quality and population health. In Australia, air quality standards are more stringent compared to standards applied in North America (Hyde et al., 2017), requiring land managers to implement best-available methods to improve estimates of the impact of smoke on air quality. Smoke emission and dispersion models that only account fine fuel consumption (one hour fuels) while ignoring combustion of CWD fuels that can smoulder for days or even weeks, are likely to seriously under-predict smoke quantity and dispersion, and consequently any fire impacts on public health. Therefore, in the absence of CWD fuel maps for the state of Victoria, the relatively coarse spatial resolution CWD fuel map developed in this project is a significant step towards reducing uncertainty in smoke dispersion modelling.

The required or desirable spatial resolution of fuel maps varies among different applications of bushfire fuels knowledge. The development of a downscaling mechanism, that allows development of finer scale resolution maps for areas of strategic importance, can be considered as a further improvement of the data-model fusion methodology for fuel mapping within Australia. Several studies have shown that terrain modelling using digital elevation models in combination with intensive fuel sampling can be applied to differentiate fuel loads between locations to improve map resolution (Keane, 2014; Keane et al., 2006; Valladares and Hott, 2008).

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.jenvman.2018.05.060.

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